Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

Research Article

Forecasting Energy Consumption in Smart Grids: A Comparative Analysis of Recurrent Neural Networks

Yasir Al-Haddad [1,*]
Information Technology Department
University of Information Technology and Communications
Baghdad, Iraq
yasir.alhaddad@uoitc.edu.iq

Abdullahi Abdu İbrahim [2]
Information Technology Department,
ALTINBAŞ UNIVERSITY
Istanbul, Türkiye
abdullahi.ibrahim@altinbas.edu.tr

Rajaa Naeem [3]
Electrical and Computer Engineering Department
ALTINBAŞ UNIVERSITY
Istanbul, Türkiye
rajaa.naeem@ogr.altinbas.edu.tr

A R T I C L E I N F O
Article History
Received: 24/04/2023
Accepted: 13/05/2024
Published:08/06/2024

ABSTRACT

In the present era of smart grids, accurate prediction of energy uses is becoming increasingly essential to guarantee optimal energy efficiency. This study contributes to the field by utilizing advanced machine learning techniques to perform predictions of energy consumption using the data from Internet of Things (IoT) devices. Specifically, the approach utilizes regression neural network (RNN) structures, such as long short-term memory (LSTM) and gated recurrent units (GRUs). The data from IoT sensors are more extensive and detailed than those of conventional smart meters, allowing for the development of more complex models of energy use patterns. This study utilizes Adam-optimized LSTM, RNN, and GRU models, along with stochastic gradient descent, to evaluate their performance in addressing the complexity of time-series data in energy forecasting on different network configurations. Result of the analysis indicates that LSTM models, which are run with the Adam optimizer, are more accurate in terms of predictions compared with the other models. This conclusion is supported the test results of these models that are within the lowest root mean square error and mean absolute error scores. All the models under the analysis exhibit signs of overfitting based on the performance indicators for the training and the testing data. This notion implies that the regularization should be utilized to ensure the improved generalizability of the models. These findings show that deep learning can have a lasting influence in improving energy consumption management systems to meet the sustainability and energy efficiency requirements. These observations are beneficial for the gradual improvements of smart grids.

Keywords:* *ADAMS, Energy Forecasting, Long Short-Term Memory, Recurrent Neural Network, Stochastic Gradient Descent.

1. INTRODUCTION

This Warming makes adaptation harder. Extreme weather occurrences are increasing, according to IPCC statistics (IPCC). Ecosystems will suffer if the global average temperature rises 1.5 °C above pre-civilization levels [1]. If nothing is done to slow the warming trend, then the global average temperature will increase by at least 2 °C by 2060 and as much as 5 °C by 2100 [2]. This situation would devastate the earth, causing biodiversity loss and food shortages [2].

Given that climate change affects the planet, a concerted effort must be exerted to dramatically reduce emissions of climate-altering gases, such as CO_2 and methane (CH_4). The energy sector’s greenhouse gas (GHG) emissions must be rapidly and significantly reduced.

Environment Germany determined that the energy sector emitted roughly 85% of Germany’s GHGs. Energy generation is responsible for half of these emissions [3]. Emissions result from energy conversion, with energy production releasing GHG and air pollution (typically during the generation of electricity or heat). These emissions also encompass emissions from vehicles and fossil fuel-heated home emissions [4], including those from factories and power plants.

Germany’s energy consumption increased to 21.5% from 1990 to 2016 to 582 billion kWh [5]. The country also reduced its electricity-related CO_2 emissions from 366 million tons to 300 million tons. Accordingly, emissions have

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

decreased relative to electricity consumption. However, fossil fuels and nuclear energy provided over 67.5% of Germany's crucial power in 2016. Approximately 133 billion kWh [5] is produced, with the majority from lignite burning, which is detrimental to the environment.

The overall CO_2 equivalent emissions of the country decreased between 1990 and 2017, with the energy sector contributed the most. In 2017, the energy sector accounted for 32% of the country's 766 million metric tons of CO_2 equivalent. This amount exceeds the transportation industry's emissions of 168 million metric tons [4].

In response to the high GHG emissions and the Paris Agreement, the EU pledged to minimize its emissions by at least 40% by 2030 compared with the 1990 levels. The EU raised its aims toward the end of 2020. The European Council has set a legally binding target of reducing emissions by at least 55% by 2030 compared with the 1990 levels [2, 6]. This GHG emission reduction method should be researched, given its potential to help mitigate climate change. Efforts should be exerted toward achieving a future where renewable energy sources meet our energy demands. In 2011, the IPCC determined that lowering energy use alone would not be enough to reverse population and income pressures [7]. Instead, current energy infrastructure necessitates a complete overhaul.

Umweltbundesamt found that converting Germany's electricity supply to 100% renewable energy by 2050 is technically possible and ecologically advantageous [8]. If this mechanism works, then we could remove all power producing GHG emissions. The GHG emissions can be significantly reduced by changing the energy distribution system. A substantial amount of work must be carried out to prepare for a renewable energy power grid before 2050. Load management, enhanced storage, and transmission infrastructure adjustments are necessary [8].

More renewable energy into electrical systems is a key climate change goal. Increase renewable energy in power systems. Renewable energy sources, such as solar, wind, and geothermal power, offer clean, long-term alternatives to fossil fuels that emit GHGs. Despite the potential of these energy sources to provide unlimited electricity, they also challenges. Renewable energy sources are more weather-dependent than fossil fuel-based ones. Long-term planning is a challenge due to the energy supply instability. Energy system operators must optimize energy supply planning. This conundrum has far-reaching effects. Always maintain energy supply-demand continuity [9].

This approach is useful and may lower deployment risks for renewable energy sources, such as wind and solar, which are rapidly developing in the energy infrastructure. Accordingly, anticipating generation and demand is essential. Energy demand forecasting remains challenging. Predictions can range from minutes to months or years (many years), making them highly versatile. This dissertation contributes to the literature on short-term load forecasting (STLF), which is used to construct low- and medium-voltage energy feeders for small and medium-sized enterprises with forecasting horizons of a few hours to a few days. Moreover, this work will utilize data from sensors surgically placed in Internet of Things devices, which are more reliable than smart meter data. Nonlinear trainable combinations are computationally costly, unlike linear forecasting models. Time-based data points are a time series.

2. BACKGROUND

Machine learning (ML)-based energy forecasting systems are being further developed. This sector has focused on electrical load and energy consumption evaluation to address supply and demand issues and environmental concerns. Energy load forecasting helps build, manage, and monitor power networks. Overestimation of demand can result in a power surplus and require additional generators, which can increase operating costs. Dependability may be compromised if the system cannot produce enough electricity to fulfill demand [10]. Home builders and manufacturers may benefit from more precise power consumption forecasts [11, 12].

ML techniques can accurately anticipate power demand [13]. Among the various ANN model types investigated are wavelet-based, long short-term memory (LSTM)-based, random forest-based, and ensemble-based [13].

Existing literature predicts energy usage using ML models. Culaba et al. [14] established a predictive analytic hybrid using K-means and SVR models. This study [15] utilized CNN and other deep learning methods to forecast future constructions' energy consumption using a fraction of the data. Pinto et al. [12] predicted workplace energy use using ensemble models. Walther and Weigold [12] studied company energy consumption literature to better understand its future.

After substantial research, several ML methods have been tested to estimate energy usage using smart meter data. Bharati et al. [15] predicted house smart meter usage using MLP and SVR models. Data gathering from the meter's consumption history includes average load, peak load, minimum load, and interior temperature.

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132
DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

These mechanisms avoid time series modeling due to the considerable number of outcomes. Han et al. [16] used smart grid analysis to study idea drift. They utilized weighted majority voting to include student results and random prediction to prevent idea drift. The recommended procedure for identifying idea drift outperformed several other, better-known methods. The results supported the recommended method. Modern smart networks address energy costs and demand forecasts, resulting in improved power grid management.

Heydari et al. [17] presented a hybrid system, including gravitational search algorithms (GSA), variational mode decomposition (VMD), and general regression neural networks. VMD analyzes intrinsic mode function (IMFS), whereas GSA selects time series features.

3. METHODOLOGY

3.1. Recurrent Neural Network (RNN)

RNNs were developed in the 1980s to represent time data. Classic neural networks independently handle inputs and outputs. Neural networks struggle with time series tasks, including financial series prediction, motor control in non-Markovian situations, and data classification (e.g., rhythm detection in music and speech). RNN efficiently models interdependent sequential datasets.

A recurrent hidden state with time-dependent activation can be added to the feed-forward neural network (cycle). RNNs depend on prior calculations; hence, its name. RNN similarly behaves on each sequence subsegment. RNNs save their calculations in "memory" for later use. RNNs cannot retrace their steps forever, but they may potentially use data from infinitely long sequences. RNNs are useful despite this limitation.

Figure 1 shows an RNN unfolding into a full network. If the sequence is five, then the network will be a five-layer neural network with each layer representing a time interval.

RNNs have constant parameters, unlike deep neural networks (U, V, and W in the equation presented earlier). RNN training is comparable to NN training. Previous calculations affect the gradient at each output in the current time step. Every time step uses RNN parameters. Vanilla RNNs trained with BPTT have trouble learning about long-term dependencies due to fading or ballooning gradients. Gating systems, such as LSTM and gated recurrent unit (GRU), can address long-term reliance. GRUs include LSTM.

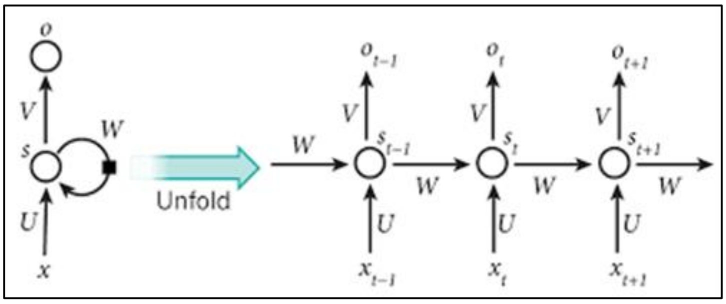

Fig. 1. RNN Structure

3.2. LSTM

Define Hochreiter's LSTM concept has been refined by several investigations. LSTM memory blocks are smaller networks with recurrent connections. Memory blocks have input, output, and forget gates. The newly incorporated gates allow the LSTM unit to discard stored information at each time step, unlike the usual recurrent unit. The typical recurrent unit differs. The LSTM avoids long-term dependability difficulties. LSTMs retain information effectively and learn rapidly. A neural network module-generated connectivity in all RNNs. Traditional RNNs have a single tanh layer or simpler recurrent module. LSTMs segment differently than repeated modules. Four neural network layers function together.

In Figure 2, each line between node tips represents a vector. Vector addition is shown by pink circles. Yellow boxes represent learned neural network layers. Forking replicates and sends a line's content to two locations, whereas concatenation connects two or more lines. The cell state, the most significant aspect of LSTMs, is the vertical line at the top. This aspect unalters all data. LSTMs can add or delete cell state information by carefully changing gates. Gates allow varying amounts of information through. Each gate uses pointwise multiplication and sigmoid neural networks.

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

The sigmoid layer calculates the percentage of each component that should pass. When the output is zero, all data are destroyed; when it is one, it is saved. Zero stores nothing. An LSTM contains three gates that monitor cell health.

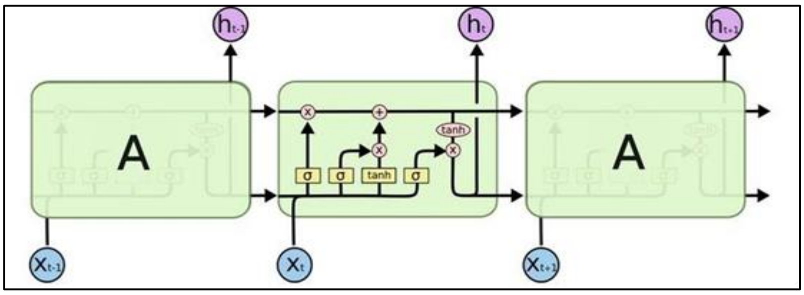

Fig. 2. LSTM Structure

3.3. GRUs

RNNs with a GRU are typically beneficial for long-range relationships because they avoid the vanishing gradient aspect of regular RNNs. A GRU's ability to selectively remember and forget data via its gating mechanisms is critical to the notion, as seen by the graphic. This photo demonstrates the complex composition of a GRU cell's two most important gates: the update and reset gates. The new hidden state is generated by these two gates with the current input and the previous hidden state. The flow of information is regulated by these two gates. The update gate determines how much of the old data the cell should recall to ensure that the GRU's outputs are solely dependent on the data in the sequence. The reset gate achieves the purpose of allowing the cell to forget unhelpful data. The GRU cell can process complex input patterns using its activation functions and applying nonlinear transformations. The dynamic system of activations and gates used by GRUs makes them particularly successful for tasks that require an understanding of sequential and time-series data.

3.4. Dataset

The Deep learning neural networks efficiently function with time series data. Neural networks may transform input data into output data utilizing datasets. This mechanism allows endless complicated model learning. Technically, input sequence contexts can help neural network models in understanding patterns and seasonality. LSTM networks outperform feed-forward networks for time series applications because they can make temporal connections without defined window widths.

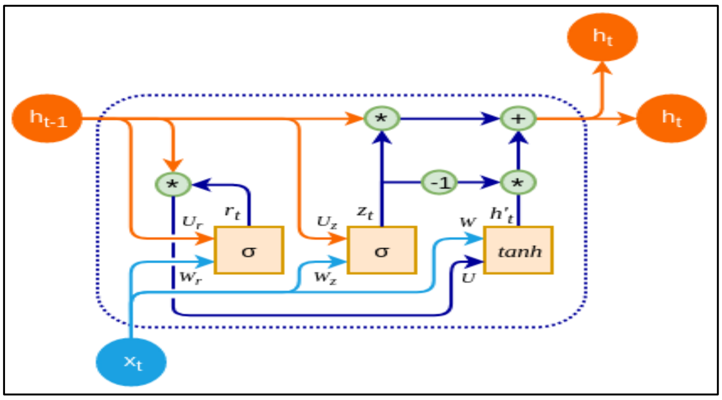

Fig. 3. GRU Structure

LSTM networks outperform feed-forward networks. We predict several time series with an LSTM model and a rudimentary RNN using the Pearson and Kendall correlation functions and Keras library. We also compare the Adam and SGD optimizers. PJM's 10 year megawatt-per-hour energy utilization confirmed our model, AEP. This dataset included residential user statistics over 12 years. The home data files include energy use and date (in MW). The RNN, LSTM, and GRU models require data cleaning and standardization before prediction.

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

Procedure:

1. This experiment uses 11,273-day data.
2. Instruction will use the first eleven hundred thousand.
3. NumPy: A NumPy array is a multidimensional, homogeneous data structure that allows for efficient numerical operations and is a fundamental component of scientific computing in Python.
4. Data for sequence length modeling are prepared.
5. Our recommended models will be trained on these data.

3.5. Overall Methodology

A flowchart depicts our study’s approach, which begins with data gathering and ends with model evaluation. In the first phase’s Start function, Python imports Numpy, Pandas, Matplotlib, and several Keras components. These libraries are used for numerical computing, data processing, and model development and training. After the necessary libraries are imported, the dataset “AEP_hourly.csv” must be read into a pandas Data Frame. Subsequently, the Datetime column must be converted to pandas datetime objects and the Data Frame indexed by this column. These processes must be completed as part of the prepare and resample data process. Data resampling to daily means will further reduce computing cost and granularity. Thereafter, the MinMaxScaler is used to scale the data values against the range of zero to one. Accordingly, the model is given the normalized input values. This step is crucial for the robust and efficient training of models that are scaled sensitive. Subsequently, the data will be in the matrix formats that are suitable for time series forecasting. This process produces a structured matrix in which each row represents unique input sequences to the model. Thereafter, the data must be properly prepared to evaluate the performance of the model on unseen data to separate the data into training and test sets. This separation ensures that the generalizability of the model is objectively assessed from the training data. The model’s technique is based on loops called “For Each Model” and “For Each Optimizer”. In this context, several models will be created using different optimizers, such as Adam and SGD, for the generate model function. The models are formed using LSTM, RNN, and GRU.

The Model Training and Evaluation portion is bounded by the dashed box. This section involves a repeatable process of fitting the model, making predictions, and calculating the metrics. After each model is fit to the training set, you will need to test it against the test set you created. After making the prediction, you will need to calculate root mean square error (RMSE) and mean absolute error (MAE) as performance metrics. The Plot Results node will help you complete the process by showing the visualization step of graphing the actual versus expected energy use. The technique moves to the Plot Loss Across Epochs after the loops are done. This process of visualizing the training process over time helps in diagnosing models that have difficulty converging. Lastly, the process is finished with the End of the methodological sequence. A flowchart is a box-and-arrow diagram that provides an overview of a methodological storyline. The computing techniques and their sequence, consisting of sequential phases and looping repetition, are summarized in a graphical format. The cyclic nature of model training and evaluation stages and the logical sequence of processes are outlined in Figure 4, which summarizes this entire technique.

4. RESULTS

This work examines and contrasts three separate neural network designs, namely, LSTM, RNN and GRU, to predict power usage. In addition, two separate optimizers, Adam and stochastic gradient descent, are utilized. The finding is illustrated by a set of graphs depicting the difference between the true second and the expected power usage of around 1600 days.

4.1. LSTM Performance

The LSTM models for training by the Adam optimizer show a close tracking of actual energy consumption trends, although some peaks are partially tracked (Figure 5). Meanwhile, the LSTM models for training by the SGD optimizer also show a similar tracking pattern of prediction, with a slightly different volatility captured in the actual data (Figure 6).

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132
DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

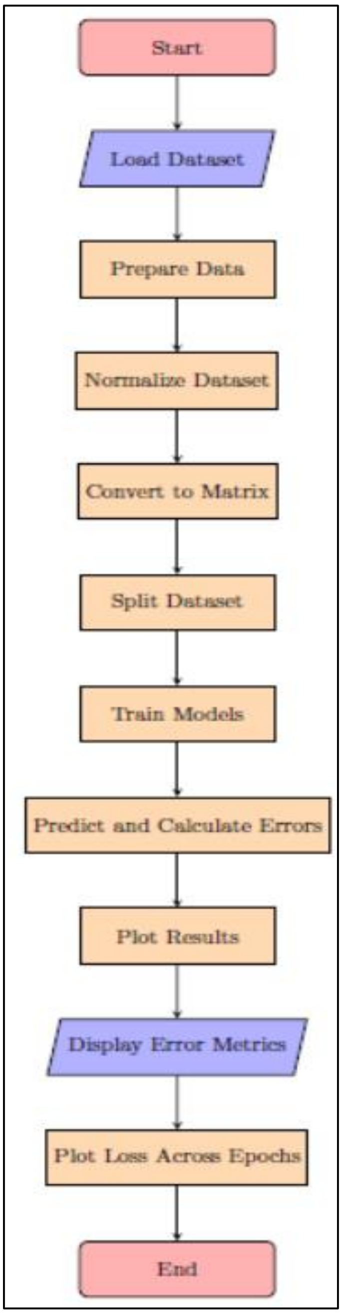

Fig. 4. Overall Methodology

4.2. RNN Performance

The RNN models trained with the Adam optimizer exhibit a reasonable prediction capacity, with the predicted values well encompassing the actual values, despite a considerable degree of noise in the predictions (Figure 7). Under SGD, the RNN's performance slightly deteriorates, as demonstrated by the increasing noise in the prediction (Figure 8).

4.3. GRU Performance

The GRU models exhibit performance analogous to the LSTM when utilizing the Adam optimizer, tightly mirroring the actual data with some discrepancies during peak values (Figure 9). The GRU models show more variability and a slight decrease in prediction smoothness with SGD, similar to the RNN (Figure 10).

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

4.4. Loss Over Epochs

The graph representing the test loss across epochs for all models and optimizers (Figure 11) indicates that the LSTM and GRU models with Adam optimizer not only converge faster but also achieve a lower loss compared with the SGD optimizer, suggesting better overall performance.

4.5. Discussion

In our comparative analysis, the models with the Adam optimizer outperform those with SGD in terms of convergence speed and stability. This observation is consistent with the theoretical underpinnings of Adam, which combines the benefits of two other extensions of stochastic gradient descent — AdaGrad and RMSProp.

A comparison table summarizing the key performance metrics, such as RMSE and MAE for each model and optimizer combination could provide a clearer perspective on the performance differences. The plots show that the GRU and LSTM models with Adam optimizer are likely to yield lower RMSE and MAE values compared with those with SGD, indicating their superior predictive accuracy and reliability for this application.

The convergence graph demonstrates the effectiveness of the Adam optimizer across all tested neural network architectures by providing consistently lower loss values. Accordingly, Adam's adaptive learning rate mechanism can be useful for the time series prediction tasks in the energy consumption domain. The data presented in performance comparison Table 1 provide a summary of how well the LSTM, RNN, and GRU models have fit the training and testing datasets when utilizing the Adam and SGD algorithms. The data have been shown with three decimal places to ensure precision.

In this case, the LSTM model combined with the Adam optimizer has slightly better fit to the training data than other models, with the lowest MAE values on the training and test sets. Accordingly, the LSTM model is efficient in capturing the patterns of energy consumption data. The RNN and GRU models have high error rates. These errors increase even more with the SGD optimizer. This result shows that the Adam optimizer could be more proficient in fine-tuning model weights for this type of data than the typical SGD algorithm. The RMSE data show a significant leap from training to test predictions for all models, indicating that all of them are overfitting on the training data, and more suitable model tuning and data regularization should be used to enhance model generalization.

TABLE I. RESULT COMPARISON

Model	Optimizer	RMSE (train)	RMSE (test)	MAE (train)	MAE (test)
LSTM	Adam	0.070	15022.113	0.053	14922.264
	SGD	0.110	15052.863	0.087	14995.446
RNN	Adam	0.069	14992.241	0.053	14894.386
	SGD	0.078	15144.826	0.061	15054.494
GRU	Adam	0.071	15212.686	0.055	15112.185
	SGD	0.101	15119.119	0.081	15050.894

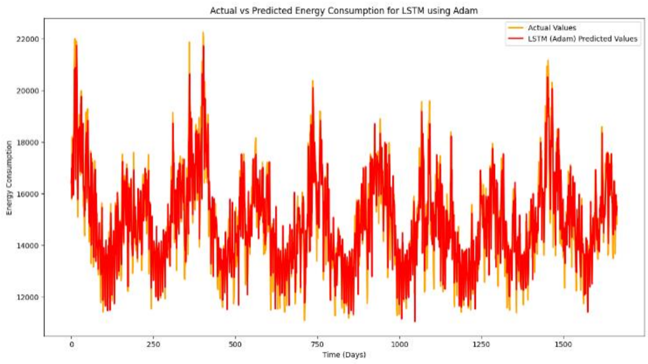

Fig. 5. . LSTM Model Predictions with the Adam Optimizer

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

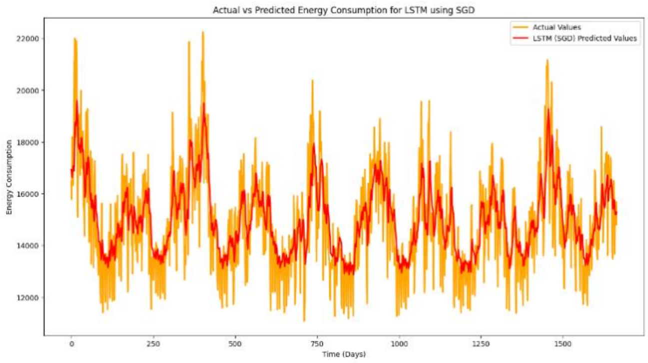

Fig. 6. LSTM Model Predictions with the SGD Optimizer

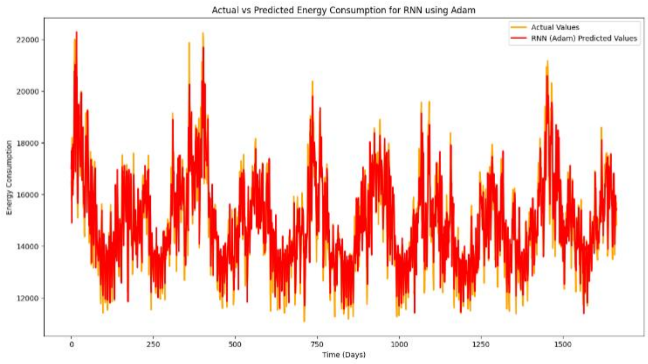

Fig. 7. RNN Model Predictions with the Adam Optimizer

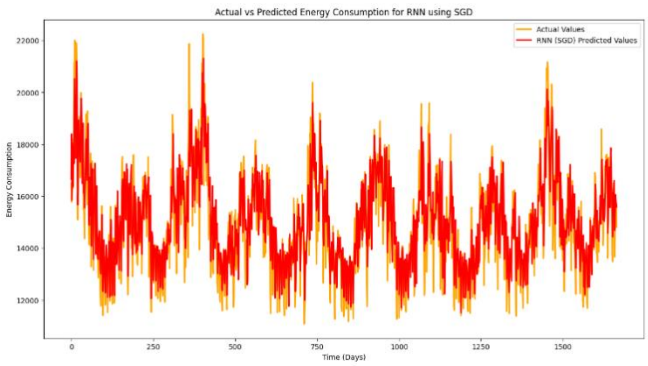

Fig. 8. RNN Model Predictions with the SGD Optimizer

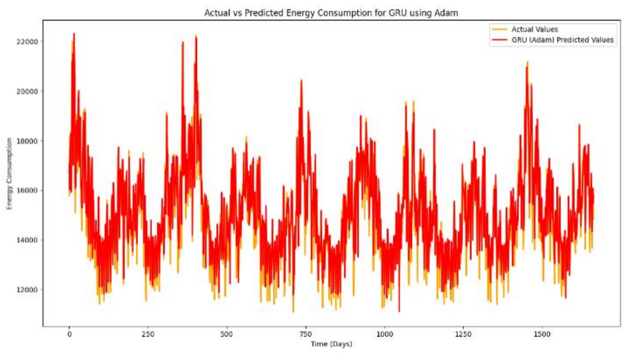

Fig. 9. GRU Model Predictions with the Adam Optimizer

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

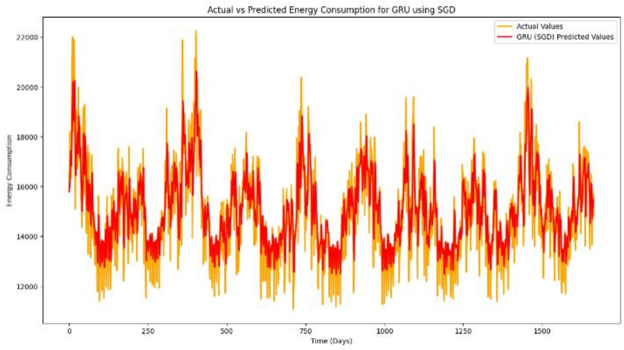

Fig. 10. GRU Model Predictions with the SGD Optimizer

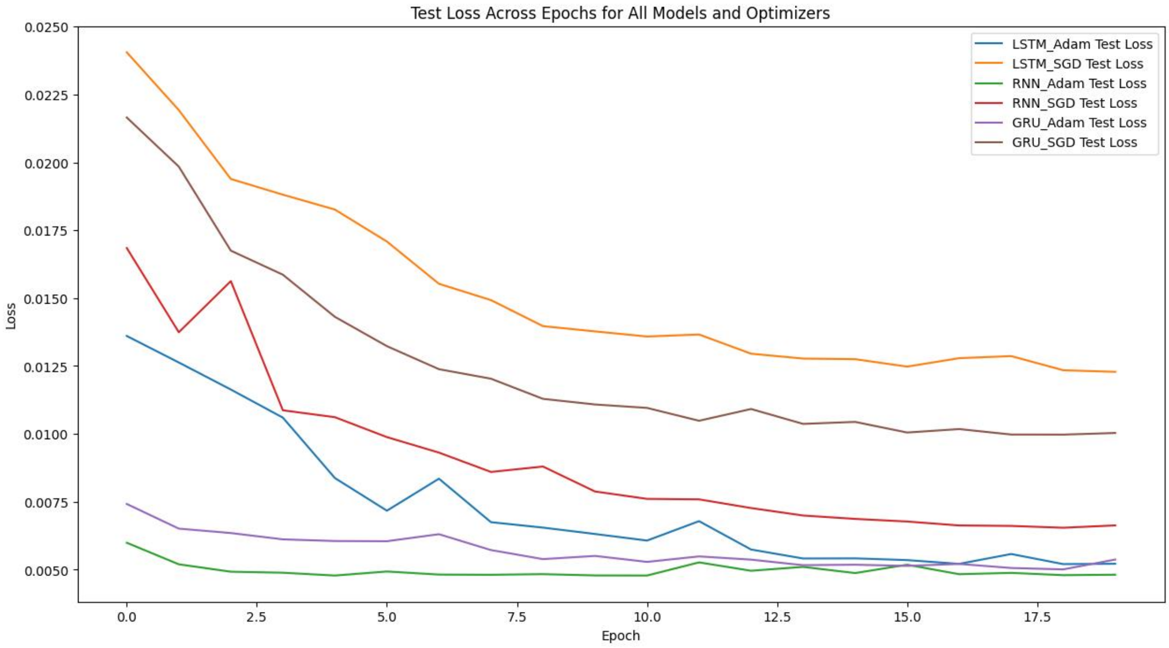

Fig. 11. Test Loss Across Epochs for all Models and Optimizers

5. CONCLUSIONS

This work focused on thoroughly exploring time-series forecasting using the capabilities of contemporary neural networks. The LSTM and GRU models have been applied to the sensitive sensor-generated data in IoT devices to improve the interpretation and achieve highly accurate energy consumption predictions. These advancements are vital for enhancing the performance of smart grids, promoting greater energy efficiency and sustainability. The results suggest that LSTM, particularly when combined with the Adam optimizer, demonstrated the most promising results by significantly mitigating the margin of error, as evidenced by the minimal RMSE and MAE values on the test set. The rest of the nonlinear models were approximated with significantly less efficacy, including the RNN and GRU frameworks, as well as the Adam and stochastic gradient descent optimizers. Nonetheless, when applying the lessons learned to the unseen data, this study found a significant discrepancy, indicating severe overfitting. This finding implies an urgent knowledge gap in the areas of regularization techniques and model tuning to advance ML and transform the models into the ones that can not only perform but also learn the consumption pattern for new data reliably, mimicking the new data pattern. These findings are valuable for future programs focused on energy consumption forecasting. This study demonstrated the profound influence that the model selection and optimization strategies have on developing an accurate and reliable predictive model. These strategies are paramount for the subsequent data-based decision-making processes in smart energy systems and beyond.

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 59, No. 1, 2024, pp. 123-132

DOI: https://doi.org/10.25195/ijci.v50i1.492
Print ISSN: 2313-190X, Online ISSN: 2520-4912

References

[1] X. Du, D. Zhou, Q. Chao, Z. Wen, T. Huhe, and Q. Liu, "Overview of low-carbon development," Overview of Low-Carbon Development, pp. 1–339, Jan. 2019, doi: 10.1007/978-981-13-9250-4/COVER.

[2] Khan, Z.A., Hussain, T., Ullah, A., Rho, S., Lee, M., Baik, S.W., "Towards Efficient Electricity Forecasting in Residential and Commercial Buildings: A Novel Hybrid CNN with a LSTM-AE based Framework", Sensors 2020, 20, 1399.

[3] Divina, F., Gilson, A., Goméz-Vela, F., García Torres, M., Torres, J.F. , "Stacking Ensemble Learning for Short-Term Electricity Consumption Forecasting", Energies 2018, 11, 949.

[4] Hadri, S., Najib, M., Bakhouya, M., Fakhri, Y., El Arroussi, M., "Performance Evaluation of Forecasting Strategies for Electricity Consumption in Buildings", Energies 2021, 14, 5831.

[5] S. Paul Sathiyan et al., "Comprehensive Assessment of Electric Vehicle Development, Deployment, and Policy Initiatives to Reduce GHG Emissions: Opportunities and Challenges," IEEE Access, vol. 10, pp. 53614–53639, 2022, doi: 10.1109/ACCESS.2022.3175585.

[6] Alberg, D., Last, M., "Short-term load forecasting in smart meters with sliding window-based ARIMA algorithms", Vietnam. J. Comput. Sci. 2018, 5, 241–249.

[7] Kourentzes, N., Barrow, D., Petropoulos, F., "Another look at forecast selection and combination: Evidence from forecast pooling", Int. J. Prod. Econ. 2019, 209, 226–235.

[8] Cassales, G., Gomes, H., Bifet, A., Pfahringer, B., Senger, H., "Improving the performance of bagging ensembles for data streams through mini-batching", Inf. Sci. 2021, 580, 260–282.

[9] J. Li, J. Hao, Q. Q. Feng, X. Sun, and M. Liu, "Optimal selection of heterogeneous ensemble strategies of time series forecasting with multi-objective programming," Expert Syst Appl, vol. 166, p. 114091, Mar. 2021, doi: 10.1016/J.ESWA.2020.11409.

[10] S. Peyghami, P. Palensky, and F. Blaabjerg, "An overview on the reliability of modern power electronic based power systems," IEEE Open Journal of Power Electronics, vol. 1, pp. 34–50, 2020, doi: 10.1109/OJPEL.2020.2973926.

[11] Culaba, A.B., Del Rosario, A.J.R., Ubando, A.T., Chang, J.S., "Machine learning-based energy consumption clustering and forecasting for mixed-use buildings", Int. J. Energy Res. 2020, 44, 9659–9673.

[12] Walther, J., Weigold, M., "A Systematic Review on Predicting and Forecasting the Electrical Energy Consumption in the Manufacturing Industry", Energies 2021, 14, 968.

[13] Chencho, J. Li, and H. Hao, "Structural damage quantification using long short-term memory (LSTM) auto-encoder and impulse response functions," Journal of Infrastructure Intelligence and Resilience, vol. 3, no. 2, p. 100086, Jun. 2024, doi: 10.1016/J.IINTEL.2024.100086.

[14] Gao, Y., Ruan, Y., Fang, C., Yin, S., "Deep learning and transfer learning models of energy consumption forecasting for a building with poor information data", Energy Build. 2020, 223, 110156.

[15] S. Bharati, P. Podder, and M. R. H. Mondal, "Visualization and prediction of energy consumption in smart homes," Int J Hybrid Intell Syst, vol. 16, no. 2, pp. 81–97, Jan. 2020, doi: 10.3233/HIS-200283.

[16] M. Han, Z. Chen, M. Li, H. Wu, and X. Zhang, "A survey of active and passive concept drift handling methods," Comput Intell, vol. 38, no. 4, pp. 1492–1535, Aug. 2022, doi: 10.1111/COIN.12520.

[17] Heydari, A., Nezhad, M.M., Pirshayan, E., Garcia, D.A., Keynia, F., De Santoli, L., "Short-term electricity price and load forecasting in isolated power grids based on composite neural network and gravitational search optimization algorithm", Appl. Energy 2020, 277, 115503.